Loading Data

Drive already mounted at /content/drive; to attempt to forcibly remoun t, call drive.mount("/content/drive", force_remount=True).

In [93]: Import pandas as pd
 import numpy as np
 import matplotlib.pyplot as plt
 %matplotlib inline
 from matplotlib.pylab import rcParams
 import seaborn as sns
 import warnings
 warnings.filterwarnings("ignore")

In [94]: path = "/content/drive/MyDrive/project/AirQualityUCI.csv"
 df = pd.read_csv(path)
 df #Preview Air Quality Dataset

Out[94]:		Date	Time	CO(GT)	PT08.S1(CO)	NMHC(GT)	C6H6(GT)	PT08.S2(NMHC)
	0	3/10/2004	18:00:00	2.6	1360	150	11.9	1046
	1	3/10/2004	19:00:00	2.0	1292	112	9.4	955
	2	3/10/2004	20:00:00	2.2	1402	88	9.0	939
	3	3/10/2004	21:00:00	2.2	1376	80	9.2	948
	4	3/10/2004	22:00:00	1.6	1272	51	6.5	836
	9352	4/4/2005	10:00:00	3.1	1314	-200	13.5	1101
	9353	4/4/2005	11:00:00	2.4	1163	-200	11.4	1027
	9354	4/4/2005	12:00:00	2.4	1142	-200	12.4	1063
	9355	4/4/2005	13:00:00	2.1	1003	-200	9.5	961
	9356	4/4/2005	14:00:00	2.2	1071	-200	11.9	1047
	9357 ı	rows × 15 d	columns					
	4							•

Classification

Out[95]: (9357, 15)

In [96]: ► df.head(100)

Out[96]:		Date	Time	CO(GT)	PT08.S1(CO)	NMHC(GT)	C6H6(GT)	PT08.S2(NMHC)	N
	0	3/10/2004	18:00:00	2.6	1360	150	11.9	1046	
	1	3/10/2004	19:00:00	2.0	1292	112	9.4	955	
	2	3/10/2004	20:00:00	2.2	1402	88	9.0	939	
	3	3/10/2004	21:00:00	2.2	1376	80	9.2	948	
	4	3/10/2004	22:00:00	1.6	1272	51	6.5	836	
	95	3/14/2004	17:00:00	2.9	1438	156	12.0	1051	

1478

1808

1898

1560

122

262

341

214

12.2

20.6

23.1

14.7

1055

1312

13811140

2.5

4.6

5.9

3.4

100 rows × 15 columns

96 3/14/2004 18:00:00

97 3/14/2004 19:00:00

98 3/14/2004 20:00:00

99 3/14/2004 21:00:00

Out[97]:

	Date	Time	CO(GT)	PT08.S1(CO)	NMHC(GT)	C6H6(GT)	PT08.S2(NMHC)	NOx(G
0	False	False	False	False	False	False	False	Fals
1	False	False	False	False	False	False	False	Fals
2	False	False	False	False	False	False	False	Fals
3	False	False	False	False	False	False	False	Fals
4	False	False	False	False	False	False	False	Fals
9352	False	False	False	False	False	False	False	Fals
9353	False	False	False	False	False	False	False	Fals
9354	False	False	False	False	False	False	False	Fals
9355	False	False	False	False	False	False	False	Fals
9356	False	False	False	False	False	False	False	Fals
9357 r	ows ×	15 colu	umns					

In [98]: ► df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9357 entries, 0 to 9356
Data columns (total 15 columns):

#	Column	Non-Null Count	Dtype
0	Date	9357 non-null	object
1	Time	9357 non-null	object
2	CO(GT)	9357 non-null	float64
3	PT08.S1(CO)	9357 non-null	int64
4	NMHC(GT)	9357 non-null	int64
5	C6H6(GT)	9357 non-null	float64
6	PT08.S2(NMHC)	9357 non-null	int64
7	NOx(GT)	9357 non-null	int64
8	PT08.S3(NOx)	9357 non-null	int64
9	NO2(GT)	9357 non-null	int64
10	PT08.S4(NO2)	9357 non-null	int64
11	PT08.S5(03)	9357 non-null	int64
12	T	9357 non-null	float64
13	RH	9357 non-null	float64
14	AH	9357 non-null	float64
d+vn	es: float64(5)	int64(8) objec	+(2)

dtypes: float64(5), int64(8), object(2)
memory usage: 1.1+ MB

In [99]: ▶ df.tail()

Out[99]:

	Date	Time	CO(GT)	PT08.S1(CO)	NMHC(GT)	C6H6(GT)	PT08.S2(NMHC)	١
9352	4/4/2005	10:00:00	3.1	1314	-200	13.5	1101	
9353	4/4/2005	11:00:00	2.4	1163	-200	11.4	1027	
9354	4/4/2005	12:00:00	2.4	1142	-200	12.4	1063	
9355	4/4/2005	13:00:00	2.1	1003	-200	9.5	961	
9356	4/4/2005	14:00:00	2.2	1071	-200	11.9	1047	
4)	•

In [100]:

df.describe()

Out[100]:

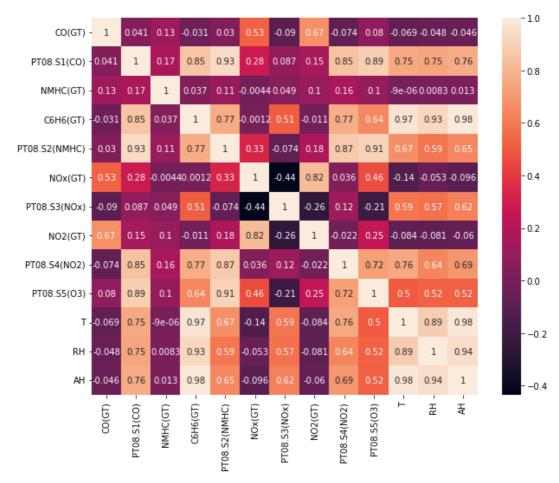
	CO(GT)	PT08.S1(CO)	NMHC(GT)	C6H6(GT)	PT08.S2(NMHC)	NOx(GT
count	9357.000000	9357.000000	9357.000000	9357.000000	9357.000000	9357.00000
mean	-34.207524	1048.990061	-159.090093	1.865683	894.595276	168.61697
std	77.657170	329.832710	139.789093	41.380206	342.333252	257.43386
min	-200.000000	-200.000000	-200.000000	-200.000000	-200.000000	-200.00000
25%	0.600000	921.000000	-200.000000	4.000000	711.000000	50.00000
50%	1.500000	1053.000000	-200.000000	7.900000	895.000000	141.00000
75%	2.600000	1221.000000	-200.000000	13.600000	1105.000000	284.00000
max	11.900000	2040.000000	1189.000000	63.700000	2214.000000	1479.00000
4						>

```
In [101]:
            M df.columns
   Out[101]: Index(['Date', 'Time', 'CO(GT)', 'PT08.S1(CO)', 'NMHC(GT)', 'C6H6(G
              T)',
                      'PT08.S2(NMHC)', 'NOx(GT)', 'PT08.S3(NOx)', 'NO2(GT)', 'PT08.S4
              (NO2)',
                      'PT08.S5(03)', 'T', 'RH', 'AH'],
                     dtype='object')
In [102]:

    df.isnull().sum()

   Out[102]: Date
                                0
              Time
                                0
                                0
              CO(GT)
              PT08.S1(CO)
                                0
              NMHC(GT)
                                0
              C6H6(GT)
                                0
              PT08.S2(NMHC)
                                0
                                0
              NOx(GT)
                                0
              PT08.S3(NOx)
                                0
              NO2(GT)
              PT08.S4(NO2)
                                0
              PT08.S5(03)
                                0
              Т
                                0
                                0
              RH
              ΑН
                                0
              dtype: int64
```

Out[103]: <matplotlib.axes._subplots.AxesSubplot at 0x7fca5ec5d430>



```
features = df.columns.tolist()[2:]
In [104]:
               features
   Out[104]:
               ['CO(GT)',
                'PT08.S1(CO)',
                'NMHC(GT)',
                'C6H6(GT)',
                'PT08.S2(NMHC)',
                'NOx(GT)',
                'PT08.S3(NOx)',
                'NO2(GT)',
                'PT08.S4(NO2)',
                'PT08.S5(03)',
                'T',
                'RH',
```

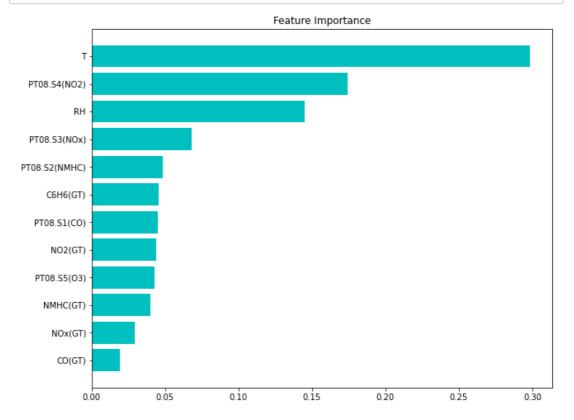
'AH']

```
X = df[features].drop('AH',1)
In [105]:
    Out[105]:
                        CO(GT) PT08.S1(CO) NMHC(GT) C6H6(GT) PT08.S2(NMHC) NOx(GT)
                                                                                            PT08.S3(N)
                     0
                            2.6
                                       1360
                                                    150
                                                              11.9
                                                                             1046
                                                                                        166
                                                                                                     11
                                       1292
                                                                              955
                     1
                            2.0
                                                    112
                                                               9.4
                                                                                        103
                                                                                                     1
                     2
                                       1402
                            2.2
                                                     88
                                                               9.0
                                                                              939
                                                                                        131
                                                                                                     1
                     3
                            2.2
                                       1376
                                                                              948
                                                     80
                                                               9.2
                                                                                        172
                                                                                                     11
                     4
                            1.6
                                       1272
                                                     51
                                                               6.5
                                                                              836
                                                                                        131
                                                                                                     1:
                    ...
                            ...
                                          ...
                                                     ...
                                                               ...
                                                                               ...
                                                                                         ...
                 9352
                            3.1
                                       1314
                                                   -200
                                                              13.5
                                                                             1101
                                                                                        472
                 9353
                            2.4
                                       1163
                                                   -200
                                                              11.4
                                                                             1027
                                                                                        353
                 9354
                            2.4
                                       1142
                                                   -200
                                                              12.4
                                                                             1063
                                                                                        293
                 9355
                            2.1
                                       1003
                                                   -200
                                                               9.5
                                                                              961
                                                                                        235
                 9356
                            2.2
                                       1071
                                                   -200
                                                              11.9
                                                                             1047
                                                                                        265
                 9357 rows × 12 columns
In [106]:
                from sklearn.preprocessing import LabelEncoder
                 le = LabelEncoder()
                 for i in df.columns:
                   if df[i].dtypes=="object":
                     df[i] = le.fit_transform(df[i])
                df.head()
    Out[106]:
                    Date Time
                                CO(GT) PT08.S1(CO) NMHC(GT) C6H6(GT) PT08.S2(NMHC)
                                                                                            NOx(GT)
                 0
                     152
                              9
                                     2.6
                                                1360
                                                             150
                                                                       11.9
                                                                                      1046
                                                                                                 166
                 1
                     152
                             10
                                     2.0
                                                1292
                                                             112
                                                                       9.4
                                                                                       955
                                                                                                 103
                 2
                     152
                             12
                                     2.2
                                                1402
                                                             88
                                                                        9.0
                                                                                       939
                                                                                                 131
                 3
                     152
                                     2.2
                                                                        9.2
                                                                                       948
                             13
                                                1376
                                                             80
                                                                                                 172
                     152
                             14
                                     1.6
                                                1272
                                                              51
                                                                       6.5
                                                                                       836
                                                                                                 131
In [107]:
                C = df.astype('int')
                 Y = C['AH']
                Y. shape
    Out[107]: (9357,)
In [108]:
                print(X.shape,Y.shape)
                 (9357, 12) (9357,)
```

```
▶ from sklearn.preprocessing import StandardScaler
In [109]:
             from sklearn.model_selection import train_test_split
             from sklearn.ensemble import RandomForestClassifier
             X train, X test, Y train, Y test = train test split(X, Y, test size = 0
             print(X_train.shape,Y_train.shape)
             print(X_test.shape,Y_test.shape)
             (6549, 12) (6549,)
             (2808, 12) (2808,)
rfc.fit(X_train,Y_train)
   Out[110]: RandomForestClassifier(n_estimators=1000)
          ▶ rfc.feature_importances_
In [111]:
   Out[111]: array([0.01930937, 0.044958 , 0.04020474, 0.04580561, 0.04818777,
                   0.02950794, 0.06783306, 0.04363222, 0.17395818, 0.042874 ,
                   0.29849471, 0.1452344 ])
          df.columns
In [112]:
   Out[112]: Index(['Date', 'Time', 'CO(GT)', 'PT08.S1(CO)', 'NMHC(GT)', 'C6H6(G
             T)',
                    'PT08.S2(NMHC)', 'NOx(GT)', 'PT08.S3(NOx)', 'NO2(GT)', 'PT08.S4
             (NO2)',
                   'PT08.S5(03)', 'T', 'RH', 'AH'],
                  dtype='object')
In [113]:
          pred = rfc.predict(X_test)
             pred
   Out[113]: array([1, 0, 1, ..., 0, 0, 1])
In [114]:
          ▶ pred.shape
   Out[114]: (2808,)
In [115]:
          ▶ | from sklearn.metrics import confusion matrix
             cm = confusion_matrix(Y_test,pred)
   Out[115]: array([[ 121,
                                        0],
                            0,
                                  0,
                       0, 1270,
                                 59,
                                        0],
                       0,
                            49, 1289,
                                        0],
                             0,
                                 17,
                                        3]])
          In [116]:
             accuracy_score(Y_test,pred)
   Out[116]: 0.9554843304843305
```

0.95419847, 0.95114504, 0.95114504, 0.96030534, 0.95565749])

	precision	recall	f1-score	support
-200	1.00	1.00	1.00	121
0	0.96	0.96	0.96	1329
1 2	0.94	0.96	0.95	1338
	1.00	0.15	0.26	20
accuracy macro avg weighted avg	0.98 0.96	0.77 0.96	0.96 0.79 0.95	2808 2808 2808



Regression

In [120]: ► df.shape #display the no of rows and columns in data set

Out[120]: (9357, 15)

Out[121]:

In [121]: ► df.head(100) #Display the first 100

	Date	Time	CO(GT)	PT08.S1(CO)	NMHC(GT)	C6H6(GT)	PT08.S2(NMHC)	NOx(GT)
0	152	9	2.6	1360	150	11.9	1046	166
1	152	10	2.0	1292	112	9.4	955	103
2	152	12	2.2	1402	88	9.0	939	131
3	152	13	2.2	1376	80	9.2	948	172
4	152	14	1.6	1272	51	6.5	836	131
95	160	8	2.9	1438	156	12.0	1051	180
96	160	9	2.5	1478	122	12.2	1055	160
97	160	10	4.6	1808	262	20.6	1312	261
98	160	12	5.9	1898	341	23.1	1381	325
99	160	13	3.4	1560	214	14.7	1140	217

100 rows × 15 columns

In [122]: ▶ df.info() # display the information related to dataset like (null value:

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9357 entries, 0 to 9356
Data columns (total 15 columns):

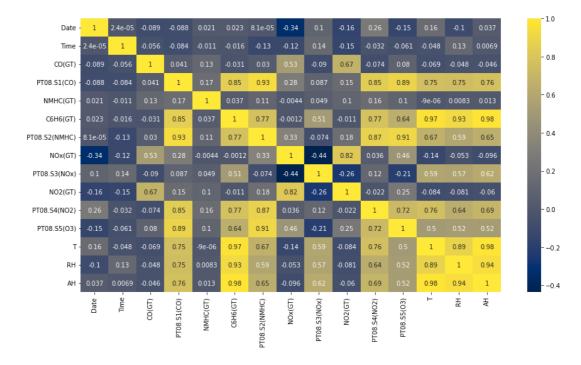
#	Column	Non-Null Count	Dtype
0	Date	9357 non-null	int64
1	Time	9357 non-null	int64
2	CO(GT)	9357 non-null	float64
3	PT08.S1(CO)	9357 non-null	int64
4	NMHC(GT)	9357 non-null	int64
5	C6H6(GT)	9357 non-null	float64
6	PT08.S2(NMHC)	9357 non-null	int64
7	NOx(GT)	9357 non-null	int64
8	PT08.S3(NOx)	9357 non-null	int64
9	NO2(GT)	9357 non-null	int64
10	PT08.S4(NO2)	9357 non-null	int64
11	PT08.S5(03)	9357 non-null	int64
12	T	9357 non-null	float64
13	RH	9357 non-null	float64
14	AH	9357 non-null	float64

dtypes: float64(5), int64(10)

memory usage: 1.1 MB

In [123]: In rcParams['figure.figsize']=(15,8) #annot -> an array of the same shape
sns.heatmap(df.corr(),annot=True, cmap = 'cividis') #to check the core

Out[123]: <matplotlib.axes._subplots.AxesSubplot at 0x7fca5cb8aeb0>



In [124]: ► df.loc[(df['T'] > 23) & (df['T'] < 24)]
df1</pre>

ut[124]:		Date	Time	CO(GT)	PT08.S1(CO)	NMHC(GT)	C6H6(GT)	PT08.S2(NMHC)	NOx(GT
	115	162	4	2.9	1417	207	14.9	1146	17
	116	162	5	2.9	1400	191	15.4	1162	15!
	119	162	8	2.8	1445	214	14.8	1141	150
	144	164	9	3.4	1447	237	17.8	1235	184
	169	166	10	7.6	1973	577	38.4	1737	41
									••
	9140	186	5	1.3	1085	-200	5.1	769	150
	9141	186	6	1.3	1177	-200	7.9	896	16!
	9187	190	4	1.4	1029	-200	3.3	670	15 ₄
	9188	190	5	1.2	1071	-200	4.8	752	13:
	9234	195	3	1.9	1136	-200	9.6	962	26
	290 rd	ws × ′	15 colu	mns					
	4								•

Linear Regression

```
In [125]:
               from sklearn.preprocessing import StandardScaler
               from sklearn.model_selection import train_test_split
               from sklearn.linear_model import LinearRegression
               from sklearn.metrics import mean_squared_error,mean_absolute_error
In [126]:
            ▶ | col=df1.columns.tolist()[2:]
               X=df1[col].drop('RH',1)
                                              #X-input features
               print(X)
                                           #y-input features
                      CO(GT)
                              PT08.S1(CO)
                                             NMHC(GT)
                                                        C6H6(GT)
                                                                   PT08.S2(NMHC)
                                                                                    NOx(GT)
               \
               115
                         2.9
                                                   207
                                                             14.9
                                      1417
                                                                             1146
                                                                                        171
               116
                         2.9
                                      1400
                                                   191
                                                             15.4
                                                                             1162
                                                                                        159
               119
                         2.8
                                      1445
                                                   214
                                                             14.8
                                                                             1141
                                                                                        156
               144
                         3.4
                                      1447
                                                   237
                                                             17.8
                                                                             1235
                                                                                        184
               169
                         7.6
                                      1973
                                                   577
                                                             38.4
                                                                             1737
                                                                                        411
               . . .
                         . . .
                                        . . .
                                                   . . .
                                                              . . .
                                                                              . . .
                                                                                        . . .
               9140
                         1.3
                                      1085
                                                  -200
                                                              5.1
                                                                              769
                                                                                        156
               9141
                         1.3
                                      1177
                                                  -200
                                                              7.9
                                                                              896
                                                                                        169
               9187
                         1.4
                                      1029
                                                  -200
                                                              3.3
                                                                              670
                                                                                        154
               9188
                         1.2
                                                  -200
                                                              4.8
                                                                              752
                                      1071
                                                                                        132
               9234
                         1.9
                                      1136
                                                  -200
                                                              9.6
                                                                              962
                                                                                        265
                      PT08.S3(NOx)
                                     NO2(GT)
                                               PT08.S4(NO2)
                                                              PT08.S5(03)
                                                                                Т
                                                                                        AΗ
                                                                             23.3
               115
                                830
                                          119
                                                        1831
                                                                       1404
                                                                                    0.9096
               116
                                838
                                          111
                                                        1829
                                                                      1263
                                                                             23.9
                                                                                    0.8757
               119
                                857
                                          110
                                                        1824
                                                                      1252
                                                                             23.8
                                                                                    0.9137
               144
                                          139
                                                                      1296
                                                                             23.9
                                                                                    0.7519
                                859
                                                        1778
               169
                                          194
                                                        2414
                                                                       2306
                                                                             23.1
                                                                                    0.7403
                                617
               . . .
                                . . .
                                          . . .
                                                          . . .
                                                                        . . .
                                                                                    1.1366
               9140
                                711
                                           85
                                                        1264
                                                                        820
                                                                             23.7
               9141
                                           94
                                                                      1011
                                                                             23.1
                                                                                    1.1523
                                616
                                                        1374
               9187
                                800
                                           87
                                                        1223
                                                                        678
                                                                             23.1
                                                                                   1.1506
               9188
                                736
                                           81
                                                        1289
                                                                        668
                                                                             23.6
                                                                                    1.1320
               9234
                                594
                                          130
                                                                       1052 23.6 0.9986
                                                        1350
               [290 rows x 12 columns]
In [127]:
            Y=df1[['RH']]
               print(Y.shape)
               print(Y)
               (290, 1)
                        RH
               115
                      32.2
                      30.0
               116
               119
                      31.3
               144
                      25.7
               169
                      26.5
               . . .
                       . . .
               9140
                      39.4
               9141
                     41.2
               9187
                      41.3
                      39.4
               9188
               9234
                      34.8
               [290 rows x 1 columns]
```

```
★ X_train, X_test, Y_train, Y_test=train_test_split(X,Y,test_size=0.3, ra)

In [128]:
              lr = LinearRegression()
              method=lr.fit(X_train,Y_train)
              method
   Out[128]: LinearRegression()
In [129]:
           ▶ print(X_train.shape, Y_train.shape)
              print(X_test.shape, Y_test.shape)
              (203, 12) (203, 1)
              (87, 12) (87, 1)
           print('Intercept:',method.intercept_)
In [130]:
              print('Slope:')
              list(zip(X.columns.tolist(),method.coef_))
              Intercept: [65.45227708]
              Slope:
   Out[130]: [('CO(GT)',
                array([ 5.57910524e-05, -7.48491353e-05, 9.37717278e-05, -2.9326146
              9e-02,
                        7.89538845e-04, 2.49416918e-04, 1.86431986e-04, -5.2637083
              9e-04,
                        3.18281110e-04, -8.45348032e-05, -2.81733277e+00, 3.4856746
              2e+01]))]
```

In [131]: Y_pred = lr.predict(X_test)
Y_pred

```
Out[131]: array([[46.18074685],
                   [57.71870774],
                   [29.00344967],
                   [55.50949218],
                   [63.18949238],
                   [63.8087211],
                   [29.34929775],
                   [47.34681429],
                   [30.41197254],
                   [47.06337823],
                   [61.69189887],
                   [60.74610137],
                   [30.65168166],
                   [35.80143346],
                   [53.46448893],
                   [38.8478863],
                  [30.49719875],
                   [27.95355679],
                   [54.50050509],
                   [62.16057164],
                   [69.49701785],
                   [39.25647342],
                   [27.69870207],
                   [43.18505741],
                   [47.40874584],
                   [51.45849307],
                   [49.89905671],
                   [34.80661818],
                   [45.57179837],
                   [28.62805561],
                   [14.02934122],
                   [44.60102385],
                   [23.28508191],
                   [38.51867483],
                   [57.0955
                               ],
                   [54.2064708],
                   [33.03190455],
                   [36.7853549],
                   [41.70839468],
                   [32.76106624],
                   [61.33594575],
                   [35.11953665],
                   [65.31368212],
                   [49.19978252],
                   [51.522501],
                   [31.46450593],
                   [29.92306114],
                   [36.2933684],
                   [26.64506587],
                   [46.55868486],
                   [64.78599824],
                   [39.66094559],
                   [37.01420839],
                   [54.51843761],
                   [42.79171121],
                   [53.83531775],
                   [48.94665302],
                   [46.63003728],
                   [27.35706972],
                   [43.26022149],
                   [27.54939613],
```

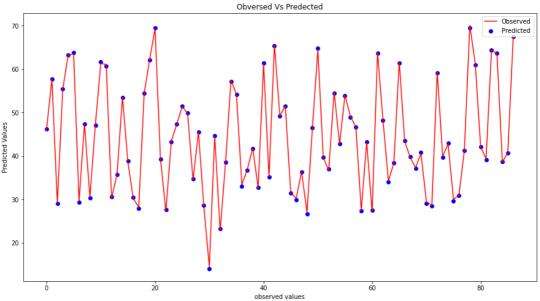
```
[63.6466169],
                      [48.22469778],
                      [34.0081318],
                      [38.39795009],
                      [61.45919855],
                      [43.49317861],
                      [39.79862297],
                      [37.09490786],
                      [40.77607815],
                      [29.10390683],
                      [28.49830661],
                      [59.19302453],
                      [39.67617633],
                      [42.9197693],
                      [29.68611482],
                      [30.89574454],
                      [41.28828584],
                      [69.55096287],
                      [60.97172957],
                      [42.09915799],
                      [39.11707659],
                      [64.43555513],
                      [63.72047282],
                      [38.68476546],
                      [40.67992711],
                      [67.49389233]])
In [132]:
              Y_pred = pd.DataFrame(Y_pred, columns = ['RH'])
               Y_pred
   Out[132]:
                         RH
                0 46.180747
                 1 57.718708
                 2 29.003450
                3 55.509492
                4 63.189492
               82 64.435555
               83 63.720473
               84 38.684765
               85 40.679927
               86 67.493892
               87 rows × 1 columns
In [133]:
               mean_sq=np.sqrt(mean_squared_error(Y_test,Y_pred))
               print('Root Mean Squared Error:',mean_sq)
```

Root Mean Squared Error: 0.22532948202734948

```
print('Mean Squared Error:',mean_squared_error(Y_test, Y_pred))
In [134]:
              Mean Squared Error: 0.050773375470713616
              print('Mean Absolute Error:',mean_absolute_error(Y_test, Y_pred))
In [135]:
              Mean Absolute Error: 0.18181574423236183
In [136]:

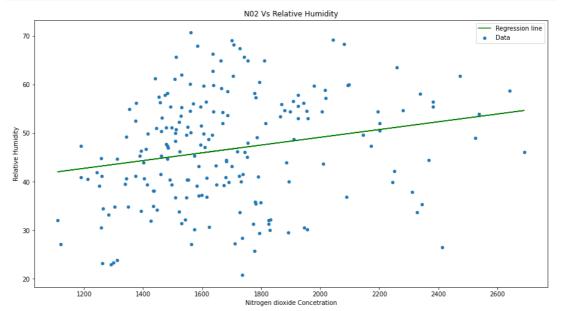
    print('Testing Accuracy:',lr.score(X_test, Y_test)*100) #Score between

              Testing Accuracy: 99.96883240890604
In [137]:
              print('Training Accuracy:',lr.score(X_train, Y_train)*100) #Score between
              Training Accuracy: 99.97385551860269
In [138]:
           plt.rcParams['figure.figsize'] = (15,8)
              x_axis = range(len(X_test))
              plt.plot(x_axis, Y_test, label = 'Observed', color = 'r')
              plt.scatter(x_axis, Y_pred, label = 'Predicted', color = 'b')
              plt.title('Obversed Vs Predected')
              plt.xlabel('observed values')
              plt.ylabel('Predicted Values')
              plt.legend()
              plt.show()
              plt.savefig('/content/drive/MyDrive/project/scatter.png')
```



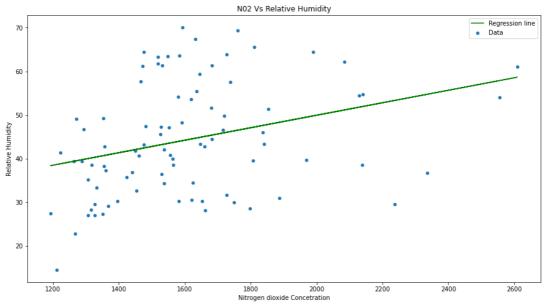
<Figure size 1080x576 with 0 Axes>

```
In [139]:  #plot for train data
    x1 = X_train[['PT08.S4(NO2)']]
    lr.fit(x1,Y_train)
    Y = lr.predict(x1)
    plt.rcParams['figure.figsize'] = (15,8)
    plt.scatter(x1, Y_train, s = 20, label = 'Data')
    plt.plot(x1, Y, color = 'green', label = 'Regression line')
    plt.title('N02 Vs Relative Humidity')
    plt.xlabel('Nitrogen dioxide Concetration')
    plt.ylabel('Relative Humidity')
    plt.legend()
    plt.show()
    plt.savefig('/content/drive/MyDrive/project/scatter.png')
```



<Figure size 1080x576 with 0 Axes>

```
In [140]: #plot for test data
    x2 = X_test[['PT08.S4(N02)']]
    lr.fit(x2,Y_test)
    Y = lr.predict(x2)
    plt.rcParams['figure.figsize'] = (15,8)
    plt.scatter(x2, Y_test, s = 20, label = 'Data')
    plt.plot(x2, Y, color = 'green', label = 'Regression line')
    plt.title('N02 Vs Relative Humidity')
    plt.xlabel('Nitrogen dioxide Concetration')
    plt.ylabel('Relative Humidity')
    plt.legend()
    plt.show()
```



Random Forest Regression

```
from sklearn.ensemble import RandomForestRegressor
In [141]:
              rf=RandomForestRegressor()
              rf
   Out[141]: RandomForestRegressor()
In [142]:
              rf_method=rf.fit(X_train,Y_train)
                                                         #fit model
              Y pred rf=rf method.predict(X test)
                                                             #predict
In [143]:
              print('Root Mean Squared Error:',np.sqrt(mean_squared_error(Y_test,Y_pr
              Root Mean Squared Error: 1.2499233953538365
              print('Mean Squared Error:',mean_squared_error(Y_test, Y_pred_rf))
In [144]:
              Mean Squared Error: 1.5623084942528631
              print('Mean Absolute Error:',mean_absolute_error(Y_test, Y_pred_rf))
In [145]:
```

Mean Absolute Error: 0.714678160919536

	Model	Mean Squared Error	Root Mean Squared Error	Mean Absolute Error
0	Linear Regression	0.050773	0.225329	0.181816
1	Random Forest Regression	1.562308	1.249923	0.714678

Clustering

In	[147]:	M	df									
	Out[14	7]:		Date	Time	CO(GT)	PT08.S1(CO)	NMHC(GT)	C6H6(GT)	PT08.S2(NMHC)	NOx(GT	
			0	152	9	2.6	1360	150	11.9	1046	160	
			1	152	10	2.0	1292	112	9.4	955	10:	
			2	152	12	2.2	1402	88	9.0	939	13	
			3	152	13	2.2	1376	80	9.2	948	17:	
			4	152	14	1.6	1272	51	6.5	836	13	
											••	
			9352	232	1	3.1	1314	-200	13.5	1101	47:	
			9353	232	2	2.4	1163	-200	11.4	1027	35	
			9354	232	3	2.4	1142	-200	12.4	1063	29:	
			9355	232	4	2.1	1003	-200	9.5	961	23	
			9356	232	5	2.2	1071	-200	11.9	1047	26	
			9357 ı	ows ×	15 co	lumns						
			4								•	
In	[156]:	M	df2 =	df.d	rop('	Date',	axis=1)					
In	[157]:	M	df2 =	<pre>df2 = df2.drop('Time', axis=1)</pre>								
In	[158]:	M	df2 =	df2.	drop('CO(GT)	', axis=1)					
In	[159]:	H	df2 =	df2.	drop('C6H6(G	T)', axis=1)				

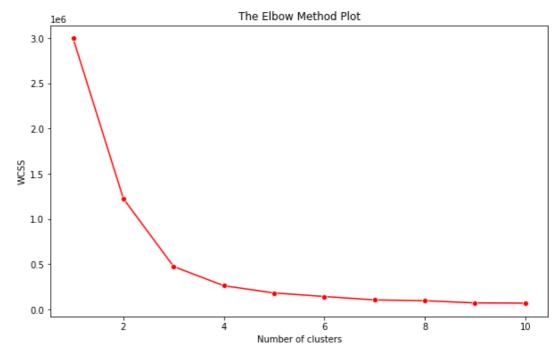
In [160]: ► df2

Out[160]:		PT08.S1(CO)	NMHC(GT)	PT08.S2(NMHC)	NOx(GT)	PT08.S3(NOx)	NO2(GT)	PT08.
	0	1360	150	1046	166	1056	113	
	1	1292	112	955	103	1174	92	
	2	1402	88	939	131	1140	114	
	3	1376	80	948	172	1092	122	
	4	1272	51	836	131	1205	116	
	9352	1314	-200	1101	472	539	190	
	9353	1163	-200	1027	353	604	179	
	9354	1142	-200	1063	293	603	175	
	9355	1003	-200	961	235	702	156	
	9356	1071	-200	1047	265	654	168	
	9357 ı	rows × 11 colu	ımns					
	4							•

Out	[161]	:
0 0. 0		

	PT08.S1(CO)	NMHC(GT)	PT08.S2(NMHC)	NOx(GT)	PT08.S3(NOx)	NO2(GT)	PT08.
1706	1379	-200	1312	267	683	179	
1987	1263	-200	1171	192	759	88	
2042	1058	-200	1134	-200	855	-200	
2080	891	-200	780	87	1110	68	
2190	938	-200	881	48	956	61	
2240	839	-200	725	36	1052	52	
2247	1123	-200	1088	157	746	92	
2343	1180	-200	1145	221	713	128	
2382	1013	-200	999	120	791	105	
2384	791	-200	658	30	1140	43	
2500	1004	-200	997	104	813	96	
2511	1277	-200	1300	331	608	136	
2574	870	-200	823	76	975	79	
2603	809	-200	628	27	1127	42	
2626	838	-200	632	24	1079	39	
2627	827	-200	656	55	1075	60	
2742	1131	-200	1087	164	705	131	
2766	1217	-200	1060	126	660	101	
2843	894	-200	709	46	997	53	
2975	1073	-200	1117	220	693	119	
3015	1211	-200	1290	311	606	156	
3030	1038	-200	1053	122	744	116	
3274	870	-200	581	15	1119	26	
3374	1281	-200	1469	287	491	136	
3421	948	-200	829	68	801	71	
3445	903	-200	648	19	975	21	
3581	1039	-200	991	93	685	74	
3609	886	-200	744	-200	869	-200	
3757	967	-200	826	68	821	61	
3990	904	-200	801	44	852	53	
4040	805	-200	637	24	1048	35	
4134	1053	-200	891	-200	690	-200	
4158	926	-200	769	-200	836	-200	
4161	832	-200	593	-200	1049	-200	
4232	944	-200	796	-200	784	-200	
4305	826	-200	504	-200	1250	-200	
4328	847	-200	634	-200	1012	-200	
4431	1202	-200	989	-200	775	-200	
4446	1251	-200	1055	-200	701	-200	

	PT08.S1(CO)	NMHC(GT)	PT08.S2(NMHC)	NOx(GT)	PT08.S3(NOx)	NO2(GT)	PT08.
4531	1289	-200	1217	-200	599	-200	
4732	1111	-200	991	218	721	109	
5065	1747	-200	1709	515	399	128	
5092	1230	-200	990	151	652	71	
5127	1055	-200	795	103	807	51	
5518	1669	-200	1615	760	404	166	
5682	1426	-200	1445	667	477	151	
8904	1315	-200	1225	518	509	193	
9093	1273	-200	988	288	563	123	
9239	1271	-200	1183	403	493	179	
9259	970	-200	710	150	833	100	
9329	1000	-200	779	171	805	115	



```
In [167]: ► df2['KMeans predicted value']=y_kmeans
```

```
In [168]: N plt.figure(figsize=(10,6))
    plt.scatter(X[y_kmeans == 0, 0], X[y_kmeans == 0, 1], c = 'brown', labe
    plt.scatter(X[y_kmeans == 1, 0], X[y_kmeans == 1, 1], c = 'green', labe
    plt.scatter(X[y_kmeans == 2, 0], X[y_kmeans == 2, 1], c = 'blue', label
    #plt.scatter(X[y_kmeans == 3, 0], X[y_kmeans == 3, 1], c = 'purple', Lat
    #plt.scatter(X[y_kmeans == 4, 0], X[y_kmeans == 4, 1], c = 'yellow', Lat
    plt.scatter(kmeans.cluster_centers_[:,0], kmeans.cluster_centers_[:, 1]
    plt.ylabel('CO(GT)')
    plt.ylabel('PT08.S3 (NOx)')
    plt.legend()
    plt.title('Clustered Data')
```

Out[168]: Text(0.5, 1.0, 'Clustered Data')

